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Forecasting models of daily maximum and minimum temperature – A comparative study for Dumdum airport

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सार – इस शोध पत्र में, दैनिक और 3 वर्षीय औसत (2001–03) अधिकतम और न्यूनतम तापमानों के पूर्वानुमान के लिए सांख्यिकीय तकनीकों नामतः सिंगल एक्सपोनेनशियल स्मूदिंग एवं ऑप्टीमाइज्ड सिंगल एक्सपोनेनशियल स्मूदिंग डबल एक्सपोनेनशियल स्मूदिंग एवं ऑप्टीमाइज्ड डबल एक्सपोनेनशियल स्मूदिंग, पद्धतियों का मौसम विज्ञान के क्षेत्र में पूर्वानुमान निदर्श के रूप में उपयोग किया गया है तथा प्राप्त हुए परिणामों की तुलना प्रचालनात्मक उपयोग के लिए इन सांख्यिकीय निदर्शों की व्यावहारिकता का पता लगाने के लिए की गई है। दो ज्ञात तकनीकों के एलगोरिथ्म में संशोधन किए गए हैं तथा दो नवीन ऑप्टीमाइज्ड तकनीकें विकसित की गई हैं। इन परिणामों से यह पता चला कि अवस्थिति और जलवायुविज्ञान की तुलना में ये पद्धतियाँ अधिक उपयुक्त हैं। इसके अलावा दैनिक वर्षा के सटीक पूर्वानुमान से अधिकतम और न्यूनतम तापमानों का पूर्वानुमान करने में सुधार हुआ है।

ABSTRACT. In this paper, statistical techniques namely, Single Exponential Smoothing and Optimized Single Exponential Smoothing, Double Exponential Smoothing and Optimized Double Exponential Smoothing were used in the field of meteorology as forecasting models for prediction of daily as well as 3-years average (2001-03) maximum and minimum temperatures and the results were compared to judge applicability of these statistical models for operational use The modifications in algorithms of the two known techniques, two new Optimized techniques are obtained. The results established that these methods are advantageous in comparison with persistence and climatology. Further the accurate prediction of daily rainfall improves forecast of the maximum and minimum temperatures.

Key words – Albedo, Exponential smoothing, Markovian probability, Neural networks, Smoothing constant, Damping constant.

1. Introduction

Temperature is one of the very important meteorological elements. The maximum temperature and minimum temperatures also provide information about heat wave conditions and cold wave conditions with information on occurrence of fog or frost formation respectively. The day's maximum temperature is generally attained in the afternoon and minimum temperature is attained in the morning hours. The day's maximum and minimum temperatures depend on the incoming short wave radiation, outgoing long wave radiation, cloud condition, albedo, rainfall and wind conditions. The impact of vegetation in the analysis of temperature forecasting and modeling was studied by correlating satellite derived NDVI values with surface maximum and minimum temperature at six sites for the years 1989-98 in NE Colorado (Hanamean Jr. *et al*., 2003). It is well known that in calm air and clear sky conditions higher maximum temperature is attained while cloud cover at night causes, higher minimum temperature.

It is also known that maximum temperature is the highest recorded temperature and minimum is the lowest recorded temperature of the day. The average of both these gives average temperature of the day and their difference gives the diurnal range of temperature. Once these two maximum and minimum temperature values are known, one can easily find out the day's average temperature, diurnal variation and may help to reconstruct the day's march of temperature as the temperature follows the sine curve from maxima to minima and again from minima to maxima.

Forecasting daily maximum and daily minimum temperature and their future values in advance play a very important role in management, planning, industry and agriculture. In the field of agriculture crop growth and development depends on maximum and minimum temperatures. In industry, the consumption of electricity depends on maximum and minimum temperatures. So the accurate forecasts of maximum and minimum temperatures are vital. Dumri *et al*. (2002) developed models for forecasting maximum and minimum temperatures during winter months (DJF), taking surface and upper air meteorological data from 1984-89 for Manali (Himachal Pradesh) in connection with natural disasters like snow avalanches in that region.

2. Data

For this study, daily maximum and minimum temperature data for three years period *viz*., 2001, 2002 & 2003 for April, May and June month in respect of station Dumdum has been collected from the records of Meteorological Office, Kolkata.

3. Forecasting methods

To forecast the maximum and minimum temperatures different forecasting techniques are employed

(*i*) *Synoptic methods*

- Identification of weather system

- Movement and dissipation of weather systems.

(*ii*) *Numerical weather prediction methods*

- Simulation of atmospheric processes with the help of mathematical equations

- Processing of the data collected from radar, satellites and other conventional means

- Choosing appropriate initial and boundary conditions.

(*iii*) *Statistical methods*

- Linear and multiple regression analysis

- Markov type probability models

- Least square trend analysis

- Moving average method

- Exponential smoothing technique.

(*iv*) *MOS methods*

- Application of statistical methods to model output from various LRF/MRF models to improvise forecasts.

(*v*) *Artificial neural network models*

- Processing of multiple weighted inputs using a suitable transfer function to obtain single output.

All the above stated methods have their own merits and demerits. At a single station Markovian probability models were employed to study sunshine and rainfall parameters (Fraedrich and Muller, 1983). Karl *et al.* (1993) their study used historical data to develop statistical models and suggested that incorporation of NWP products and weather elements such as rain, thunderstorm and strong surface winds could reduce cases of large forecast errors of minimum/maximum temperature prediction. Artificial Neural Network models have been used in agro-ecological and meteorological modeling (Arca *et al*., 1988). Statistical methods are simple to use, easy to understand and do take less computational time. The NWP models are complicated but highly useful for now-casting and short-term forecasting. The AAN models are easier to use than the NWP models. Lastly, it is known that the synoptic methods are often subjective and sometimes may lead to biased forecasts. Daily climatology of maximum and minimum temperatures and accumulated precipitation studied using Model Output Statistics (MOS) from NCEP models by calculating and evaluating forecasts using cross validation methods and found that the MOS forecasts are advantageous over persistence and climatology models (Kim *et al.* 2001) Massie and Rose (1997) found that the auto regression forecasting method was useful in making subjective improvement to (MOS) from Nested Grid Model (NGM) by studying the relationship between forecast geo-potential-thickness and observed maximum temperature by regression equation for Nashville.

Forecasts of all ranges short, medium and long range play crucial role in every field of human activity provided the issued forecasts are timely and accurate. Often such forecasts are issued using both qualitative and quantitative methods. In quantitative methods, a mathematical model is used to generate forecast of the future value of the parameter chosen. Time series method is a well known quantitative method. In time series method, forecast is based on the past as well as current observation and it is used to study the underlying structure of any given set of data and the same idea is utilized to forecast the future value. Several models were proposed based on the statistical analysis of relationship between daily minimum temperature and other meteorological parameters observed at Sunset at other hours of the day (Allen, l957 Young, 1920). Raible *et al.* (1998) introduced and applied two statistical short-term forecast schemes (*i*) Multiple regression (*ii*) Markovian model to Central European Weather stations for real - time prediction and found that these techniques provide potential for future applications in operational weather forecasting.

4. Methodology

In this paper, statistical technique such as single exponential smoothing, optimized single exponential smoothing , double exponential smoothing and optimized double exponential smoothing are employed as forecasting models for prediction of daily maximum and minimum temperatures and also for prediction of 3-years average daily maximum and minimum temperatures in case of the selected station. Thus, a total of data sets and 3 average data sets are subjected to these models.

(*i*) *Single exponential smoothing (SES)*

Generally, the single exponential smoothing model requires a most recent actual value, the most recent forecast generated on the basis, of prior value and a smoothing constant whose value lies between 0 and 1. The single exponential smoothing forecast model is $F_t = \alpha Y_{t-1} + (1 - \alpha) F_{t-1}$ where 'F_t' is Exponential smoothed forecast for the period t. 'F_{t-1}' is the Exponential smoothed forecast for the period (t-1). 'Y_{t-1}' is the actual value of prior period and 'α' is the smoothing constant. Here, the new forecast is the old forecast plus an adjustment for the error that occurred in the last forecast. If in the basic model equation, smoothing constant 'α' is taken as zero then the new forecast would simply be equal to old forecast and if the smoothing constant takes a value equal to one, then the new forecast is equal to actual value of the prior period. Therefore, the smoothing constant to be, chosen such that the value suits to the time series well and so that it's value lies in between 0.1 and 0.9. This model gives good result on a data set with no trend.

(*ii*) *Optimized single exponential smoothing method (OSES)*

The basic model equation is same as the single exponential smoothing method except that different values of smoothing constant are used to generate new forecast - in order to minimize the difference between actual value and the forecast value.

(*iii*) *Double exponential smoothing method (DES)*

In this technique two constants are used instead of a single constant used in SES to account for any hidden trend in the time series. It is known that Single Exponential Smoothing (SES) method forecasts lag behind the observations if upward or downward trend is present in the data and if the trend is not accounted for the forecast values may be inaccurate. Therefore, two constants 'α ' and 'γ' are chosen in conjunction with each other. Here, the first constant 'α' weighs current data compared to past data. To start with, 'b_{t-1}' is chosen as the initial trend which is the difference of previous values and 'b_t' is the updated trend by taking into account the difference between two periods. The 'γ' parameter assesses the weight of current data and previous data. The basic model equations are

$$F_t = \alpha Y_{t-1} + (1 - \alpha)(F_{t-1} + b_{t-1}) \quad (1)$$

$$b_t = \gamma (F_t - F_{t-1}) + (1 - \gamma) b_{t-1} \quad (2)$$

where $0 \leq \alpha \leq 1$ and $0 \leq \gamma$ 1. The second equation smoothes the values obtained from the first equation. The second equation of the model is utilized for smoothing trend and the current value of the series is used to obtain its smoothed value for replacement in the forecast equation given as model equation (1). Several methods are there to choose initial forecast value. The first smoothing equation adjusts the new forecast directly for the trend of the previous period, b_{t-1}, by adjusting it to the last smoothed forecast value. This helps to eliminate lag and to bring the new forecast to a base value. The second equation again updates the trend, which is taken as the difference between the last two values and the smoothed value is again utilized in first equation as prior forecast value.

(*iv*) *Optimized double exponential smoothing method (ODES)*

The basic model equations are same as the double exponential smoothing method except the fact that out of the number of new forecast generated from different values of two constants, the forecast whose difference with actual is minimum is retained as new forecast in subsequent computations.

5. Results and discussion

The forecasts of daily maximum and minimum temperatures generated through the four models developed *viz*., Single exponential smoothing (SES), optimized single exponential smoothing (OSES), double exponential smoothing (DES), optimized double exponential smoothing (ODES) for each of the three months in 3 years period (2001-03) were compared. In order to compute the SES forecasts the value of the smoothing constant (α) was chosen as 0.87 and for the DES forecast computations the smoothing constant (α) value has been selected as 0.92 and damping constant, (γ) value has been selected as 0.81. In SES, OSES, DES and ODES forecasting models the initial value of the forecast has been taken equal to the initial actual value and

TABLE 1

Showing average daily maximum temperature (2001-03) observed and forecast from models

	April						May						June				
Day	Raw	SES	OSES	DES	ODES	Day	Raw	SES	OSES	DES	ODES	Day	Raw	SES	OSES	DES	ODES
1	34.9	34.9	34.9	34.9	34.9	1	34.4	34.4	34.4	34.4	34.4	1	35.9	35.9	35.9	35.9	35.9
2	34.4	34.9	34.9	34.9	34.4	2	35.7	34.4	34.4	34.4	34.8	2	36.0	35.9	35.9	35.9	35.8
3	32.2	34.5	34.5	34.4	33.9	3	35.9	35.5	35.6	35.6	35.3	3	36.3	36.0	36.0	36.0	35.8
4	33.3	32.5	33.3	32.3	33.3	4	35.8	35.9	35.8	35.9	35.8	4	34.9	36.3	36.0	36.3	35.6
5	35.1	33.2	33.2	33.1	32.7	5	36.8	35.8	35.9	35.8	36.2	5	34.5	35.1	35.0	35.0	35.4
6	36.3	34.9	34.9	35.0	34.8	6	34.5	36.7	35.9	36.7	36.7	6	35.9	34.6	35.0	34.5	35.1
7	36.8	36.1	36.2	36.3	36.6	7	35.2	34.8	35.2	34.7	36.8	7	36.1	35.7	35.8	35.7	35.0
8	37.4	36.7	36.7	36.8	37.4	8	36.1	35.1	35.2	35.0	36.1	8	35.3	36.1	35.8	36.1	35.3
9	35.8	37.3	36.8	37.4	38.1	9	35.1	36.0	35.2	36.0	35.6	9	34.1	35.4	35.4	3554	35.2
10	35.7	36.0	36.0	36.0	36.2	10	35.2	35.2	35.2	35.2	35.1	10	35.0	34.3	35.0	34.2	35.0
11	35.4	35.7	35.7	35.6	34.9	11	34.4	35.2	35.2	35.2	34.5	11	34.2	34.9	34.3	34.8	34.8
12	35.2	35.4	35.4	35.4	35.2	12	35.8	34.5	35.1	34.4	34.4	12	32.8	34.3	34.3	34.3	34.5
13	34.6	35.2	35.2	35.2	34.8	13	35.3	35.6	35.3	35.6	35.2	13	32.9	33.0	32.9	32.9	33.0
14	34.1	34.7	34.7	34.6	34.3	14	35.3	35.3	35.3	35.4	35.2	14	33.0	32.9	32.9	32.9	31.6
15	34.3	34.2	34.3	34.1	34.1	15	34.7	35.3	35.3	35.3	35.2	15	34.1	33.0	33.0	33.0	32.7
16	35.2	34.3	34.3	34.2	34.1	16	35.8	34.8	35.2	34.7	35.1	16	33.5	34.0	33.5	34.0	32.1
17	35.7	35.1	35.1	35.1	35.0	17	36.8	35.7	35.7	35.7	35.1	17	33.0	33.6	33.5	33.6	32.8
18	34.0	35.6	35.2	35.7	35.1	18	36.8	36.7	36.7	36.8	36.6	18	30.0	33.1	33.1	33.0	32.1
19	36.1	34.2	35.5	34.2	35.1	19	37.8	36.8	36.8	36.8	36.8	19	32.6	30.4	32.7	30.2	31.2
20	36.2	35.9	35.9	35.9	35.2	20	39.8	37.7	37.7	37.7	37.7	20	33.4	32.3	32.4	32.2	30.6
21	37.2	36.2	36.2	36.2	36.1	21	38.5	39.5	38.5	39.7	38.6	21	32.5	33.3	32.5	33.4	32.4
22	35.9	37.1	36.3	37.2	36.4	22	36.6	38.6	38.6	38.7	39.4	22	30.3	32.6	32.6	32.7	32.0
23	36.5	36.1	36.5	36.1	36.5	23	36.5	36.9	36.8	36.7	37.0	23	31.8	30.6	31.9	30.5	31.5
24	36.9	36.4	36.5	36.4	36.7	24	34.5	36.5	36.5	36.5	35.0	24	32.2	31.6	31.7	31.5	31.1
25	36.9	36.8	36.9	36.9	36.8	25	35.4	34.8	35.3	34.6	34.4	25	32.1	32.1	32.1	32.2	32.0
26	36.3	36.9	36.9	36.9	37.0	26	36.1	35.3	35.3	35.2	34.4	26	31.9	32.1	32.1	32.2	32.2
27	36.5	36.4	36.5	36.4	36.5	27	36.5	36.0	36.0	36.0	35.3	27	33.7	31.9	32.1	31.9	32.3
28	36.8	36.5	36.5	36.5	36.6	28	36.3	36.4	36.3	36.5	35.9	28	33.8	33.5	33.5	33.5	32.5
29	37.0	36.8	36.8	36.8	36.7	29	36.6	36.3	36.4	36.4	36.4	29	33.2	33.8	33.5	33.9	33.2
30	35.6	37.0	36.8	37.0	36.8	30	36.4	36.6	36.4	36.6	36.6	30	32.0	33.3	33.3	33.3	33.8
1*	?	35.8	35.7	35.7	36.8	31	36.9	36.4	36.6	36.4	36.9	1*	?	32.2	32.1	32.1	32.2
						1*	?	36.8	36.5	36.9	36.9						

1* is the 1st day of subsequent month.

subsequent forecasts were generated. In DES and ODES forecasting models, the initial value of ‘b has been taken equal to $[(y_2 - y_1) + (y_3 - y_2) + (y_4 - y_3)] / 3.0$ and the subsequent forecasts were generated. Here, ‘y’ values are raw observations and the initial value of ‘b_{t-1}’ is equal to $(y_4 - y_1) / 3.0$ and generalizes to $(y_n - y_1) / (n-1)$. In ODES model, of the new forecasts generated from different values of smoothing constant, the forecast which has

TABLE 2

Showing average daily minimum temperature (2001-03) observed values and forecast from models

	April						May						June				
Day	Raw	SES	OSES	DES	ODES	Day	Raw	SES	OSES	DES	ODES	Day	Raw	SES	OSES	DES	ODES
1	25.0	25.0	25.0	25.0	25.0	1	23.6	23.6	23.6	23.6	23.6	1	24.7	24.7	24.7	24.7	24.7
2	24.0	25.0	25.0	25.0	24.6	2	24.8	23.6	23.6	23.6	23.7	2	27.8	24.7	24.7	24.7	24.8
3	22.8	24.1	24.1	24.1	24.2	3	25.5	24.6	24.7	24.7	23.9	3	27.4	27.4	27.5	27.7	25.5
4	23.7	23.0	23.7	22.8	23.7	4	24.0	25.4	24.8	25.5	24.2	4	25.1	27.4	27.4	27.6	25.9
5	24.5	23.6	23.6	23.5	23.3	5	27.4	24.2	25.3	24.2	24.4	5	26.8	25.4	26.7	25.3	26.1
6	23.9	24.4	23.9	24.5	23.8	6	25.5	27.0	25.4	27.1	24.9	6	25.5	26.6	25.5	26.5	26.4
7	24.4	24.0	24.4	24.0	24.3	7	25.9	25.7	26.0	25.8	25.3	7	27.7	25.6	26.5	25.6	26.5
8	25.5	24.3	24.4	24.4	24.7	8	26.5	25.9	25.9	25.8	25.8	8	25.7	27.4	25.8	27.5	26.8
9	25.2	25.3	25.2	25.4	25.2	9	24.5	26.4	25.9	26.4	26.2	9	26.0	25.9	26.0	26.0	26.8
10	26.5	25.2	25.4	25.3	25.6	10	24.8	24.7	24.9	24.7	26.2	10	26.3	26.0	26.0	26.0	26.5
11	24.7	26.3	25.3	26.4	26.1	11	24.9	24.8	24.8	24.7	25.1	11	26.7	26.3	26.3	26.3	26.6
12	25.3	24.9	25.4	24.9	26.2	12	25.1	24.9	24.9	24.9	24.9	12	26.4	26.6	26.4.	26.7	26.7
13	24.4	25.2	24.9	25.2	25.6	13	26.7	25.1	25.1	25.1	24.8	13	27.1	26.4	26.6	26.5	26.8
14	24.7	24.5	24.7	24.5	25.2	14	27.2	26.5	26.5	26.6	26.5	14	26.8	27.0	26.8	27.0	26.9
15	24.6	24.7	24.6	24.6	24.7	15	25.6	27.1	26.6	27.2	26.6	15	26.6	26.8	26.8	26.9	27.0
16	24.9	24.6	24.7	24.6	24.3	16	25.8	25.8	25.8	25.8	26.6	16	27.2	26.6	26.8	26.6	27.0
17	24.8	24.9	24.8	24.9	24.8	17	26.3	25.8	25.8	25.7	26.3	17	26.4	27.1	26.7	27.1	27.1
18	25.4	24.8	24.9	24.8	25.1	18	26.7	26.2	26.2	26.2	26.3	18	26.2	26.5	26.5	26.5	27.1
19	26.1	25.3	25.3	25.4	25.5	19	27.5	26.6	26.7	26.7	26.4	19	26.5	26.2	26.4	26.2	26.5
20	26.3	26.0	26.0	26.1	25.9	20	28.0	27.4	27.4	27.5	27.4	20	27.2	26.5	26.5	26.4	26.0
21	26.9	26.3	26.3	26.3	26.3	21	26.4	27.9	27.5	28.0	27.6	21	26.5	27.1	26.5	27.2	26.5
22	26.2	26.8	26.3	26.9	26.7	22	25.4	26.6	26.6	26.6	27.7	22	25.9	26.6	26.6	26.6	26.1
23	25.1	26.3	26.3	26.3	27.0	23	25.0	25.6	25.5	25.4	25.6	23	25.2	26.0	26.0	25.9	25.7
24	26.5	25.3	26.1	25.2	26.5	24	26.0	25.1	25.5	25.0	25.4	24	25.3	25.3	25.3	25.2	25.3
25	25.3	26.3	25.3	26.3	26.1	25	24.2	25.9	25.1	25.9	25.3	25	26.4	25.3	25.3	25.2	25.0
26	26.8	25.4	26.3	25.4	25.7	26	27.9	24.4	25.7	24.4	25.1	26	26.3	26.3	26.3	26.3	26.2
27	25.1	26.6	25.5	26.6	25.4	27	25.8	27.4	25.8	27.5	25.6	27	26.7	26.3	26.3	26.4	27.2
28	26.8	25.3	26.5	25.3	25.1	28	24.8	26.0	26.0	26.1	25.5	28	27.0	26.6	26.7	26.1	27.0
29	27.6	26.6	26.6	26.6	25.0	29	27.8	25.0	25.9	24.9	25.4	29	26.6	27.0	26.7	27.0	26.9
30	26.6	27.5	26.7	27.6	26.5	30	26.7	27.4	26.6	27.5	25.8	30	27.3	26.6	26.9	26.7	26.8
1*	?	26.7	26.7	26.8	26.6	31	26.7	26.8	26.8	26.9	26.3	1*	?	27.2	26.7	27.2	26.8
						1*	?	26.7	26.7	26.7	26.5						

1* is the 1st day of subsequent month.

minimum difference with the actual value is retained as the second forecast to compute subsequent forecasts. The results showed that the OSES forecasts were better than SES forecasts and ODES forecasts were better than the DES forecasts. Overall OSES forecasts are accurate among all the four models for the selected station.

(*i*) Maximum temperature forecasts for the month of April given by the SES model were within 1-2° C from the observed value in 75% - 50% cases and within 2-3° C from the observed value in 90% - 75% cases. At the same time, OSES forecasts in 84% - 67% cases were within 1 - 2° C and 97% - 84% cases were within 2 - 3° C. DES

TABLE 3

Showing daily minimum and maximum temperature forecasts from models lie within specified range from the observed values for each of the three months in the period 2001-03

Model	Number of cases (%)											
	Minimum						Maximum					
	1-2° C			2-3° C			1-2° C			2-3° C		
	April	May	June	April	May	June	April	May	June	April	May	June
SES	50	50-33	80-70	75-67	70-60	90	75-50	67-43	57-40	90-75	84-77	87-75
OSES	70-57	50-33	80	90-83	83-70	90	84-67	67-50	70-58	97-84	97-87	93-77
DES	50-40	50-33	80	80-60	70-50	90	70-50	58-44	58-38	90-75	84-77	84-70
ODES	67-50	50-33	80	84-67	70-50	90	75-50	70-48	64-58	90-75	84-77	84-70

forecasts were within 1-2° C from the observed value in 70% - 50% cases and within 2 - 3° C from the observed value in 90% - 75% cases. Similarly, ODES forecasts were with in 1 - 2° C in 75% - 50% cases and within 2 - 3° C in 90% - 75% cases (Table 3).

(*ii*) Maximum temperature forecasts for the month of May given by SES model were within 1 - 2° C from the observed value in 67% - 43% cases and were within 2 - 3° C in 84% - 77%. The OSES forecasts were within 1 - 2° C in 67% - 50% cases and within 2-3°C in 97% - 87% cases. The DES forecasts in 58% - 44% cases were within 1-2° C and in 84% - 77% cases were within 2-3° C from the observed value. The ODES forecasts in 70% - 48% cases were within 1-2° C and in 84% - 77% cases were within 2 - 3° C (Table 3).

(*iii*) Maximum temperature forecasts for the month June, given by SES model were within 1 - 2° C in 57% - 40% cases and were within 2 - 3° C in 87% - 75% cases. The OSES forecasts were within 1 - 2° C in 70% - 58% cases, and were within 2 - 3° C in 93% - 77% cases. The DES forecasts in 58% - 38% cases were within 1 - 2° C and 84% - 70% cases were within 2 - 3° C from the observed value. The ODES forecasts were within 1-2°C in 64%-58% cases and were within 2 - 3° C in 84% - 70% cases (Table 3).

(*iv*) Minimum temperature forecasts for the month of April given by SES model were within 1 - 2° C in 50% cases and were within 2 - 3° C in 75% - 67% cases. The OSES forecasts were within 1 - 2° C in 70% - 57% cases and were within 2 - 3° C in 90% - 83% cases. The DES forecasts in 50% - 40% cases were within 1 - 2° C and 80% - 60% cases were within 2 - 3° C from the observed value. The ODES forecasts were within 1 - 2° C in 67% - 50% cases and were within 2 - 3° C in 84% - 67% cases (Table 3).

(*v*) Minimum temperature forecasts for the month of May given by SES model were within 1 - 2° C in 50% - 33% cases and were within 2 - 3° C in 70% - 60% cases. The OSES forecasts were within 1 - 2° C in 50% - 33% cases except for the year 2001 where the forecasts were within 1 - 2° C in 70% cases and were within 2 - 3° C in 83% - 70% cases. The DES forecasts in 50% - 33% cases were within 1 - 2° C and 70% - 50% cases were within 2 - 3° C from the observed value. The ODES forecasts were within 1 - 2° C in 50% - 33% cases and were within 2 - 3° C in 70% - 50% cases (Table 3).

(*vi*) Minimum temperature forecasts for the month of June, given by SES. model were within 1 - 2° C in 80% - 70% cases and were within 2 - 3° C in 90% cases. The OSES forecasts were within 1 - 2° C in 80% - 70% cases and were within 2 - 3° C in 90% cases. The DES forecasts in 80% - 70% cases were within 1 - 2° C and 90% cases were within 2 - 3° C from the observed value. The ODES forecasts were within 1 - 2° C in 80% - 70% cases and were within 2 - 3° C in 90% cases (Table 3).

(*vii*) The computed average daily maximum temperature (2001-03) from the observed values alongwith the forecasts of average daily maximum temperature from four models used in this paper for three individual months namely, April, May and June were presented in Table 1 for the purpose of comparison. It is seen from the Table 4 that for the average daily maximum temperature, computed out of the 3 years period (2001-03); the model forecasts accuracy has improved and for the month of April, the SES/OSES/DES/ODES forecasts were within 1 - 2° C from the observed value in 75%/84%/75%/77% cases respectively and were within 2 - 3° C from the observed value in 97%/97%/94%/94% cases respectively. For the month of May, the forecasts generated from the models SES/OSES/DES/ODES were within 1 - 2° C from the observed value in 84%/84%/70%/75% cases respectively and were within 2 - 3° C from the observed

TABLE 4

Showing average daily maximum and minimum temperature forecasts from models lie within the specified range from the observed values for each of the three months in the period 2001-03

Model	Number of cases (%)											
	Minimum						Maximum					
	1-2° C			2-3° C			1-2° C			2-3° C		
	April	May	June	April	May	June	April	May	June	April	May	June
SES	70	54	77	100	90	90	75	84	64	97	94	90
OSES	90	70	87	100	94	94	84	80	75	97	97	94
DES	70	50	80	100	90	90	75	70	64	94	90	90
ODES	84	60	80	100	90	94	77	75	64	94	90	94

value in 94%/97%/90%/90% cases. For the month of June, the forecasts from the models SES/OSES/ DES/ODES were within 1 - 2° C from the observed value in 64%/75%/64%/64% cases respectively and were within 2 - 3° C from the observed value in 90%/94%/90%/94% cases. It seen that the decrease in accuracy of forecast values from SES/OSES/DES/ODES for the month of June which are within 1 - 2° C is due to inherent nature of data which showed more fluctuations compared to the months of April and May but not due to less number of raw data for the month of June.

(*viii*) The computed average daily minimum temperature (2001-03) from the observed values along with the forecasts of average daily minimum temperature from the four models used in this paper for three individual months namely, April, May and June were presented in Table 2 for the purpose of comparison. It is seen from the Table 4 that for the average daily minimum temperature, computed out of the 3 years period (2001-03), for the month of April, the SES/OSES/DES/ODES forecasts were within 1 - 2° C from the observed value in 70%/90%/ 70%/84% cases respectively and were within 2 - 3° C from the observed value in 100%/100%/100%/100% cases respectively. For the month of May, the forecasts generated from the models SES/OSES/DES/ODES were within 1 - 2° C from the observed value in 54%/70%/ 50%/60% cases respectively and were within 2 - 3° C from the observed value in 90%/94%/94%/94% cases. For the month of June, the forecasts from the models SES/OSES/DES/ODES were within 1 - 2° C from the observed value in 77%/87%/80%/80% cases respectively and were within 2 - 3° C from the observed value in 90%/ 94%/90%/94% cases.

6. Conclusions

The model forecasts were encouraging and the models gave best results in the data set where fluctuations were not high. It is also seen that during the days of thunderstorms or heavy precipitation, the maximum temperature fell by more than 8° C and in some cases by 3 - 4° C and in such cases the forecasts from these models are lagging behind and incorporation of precipitation forecasts into these models may improve the forecasts. The model forecasts can be improved subjectively based on forecasts of other meteorological parameters that influence the maximum and minimum temperatures or by incorporating model forecasts of the same into these forecasting models. Those forecasts whose errors are slightly more than 2° C can be brought within 2° C by suitably adjusting the initial value and constants used. It is noticed that this method is definitely advantageous over persistence and climatology method and accuracy of these model forecasts can be improved by changing the origin based on the first run output. Furthermore, it is concluded that these models need to be improved from time to time and place to place obtain desired results.

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